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Passive Differential Matched-field Depth Estimation of Moving Acoustic Sources

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Passive Moving Target Depth Estimation (MTDE)

OBJECTIVE: To discriminate submerged versus surface targets by exploiting changes in the spatial wavefront at the array due to multipath propagation from a moving source.

BACKGROUND:

- Conventional matched-field processors use a computational model to predict the relative phase and amplitude between multipath arrivals from a distant stationary source and thus are very sensitive to horizontal wavenumber differences multiplied by range.
- Target motion in classical MFP techniques is problematic since it tends to decorrelate multipath components over the observation times used with stationary source models.
- Previous work using moving sources has attempted to mitigate source motion effects by pre-processing so as to effectively remove target dynamics.
- Proposed work aims to exploit target dynamics to estimate source depth and range-rate without requiring the accurate environmental models required for range estimation.
- Joint depth-range-rate estimation should achieve robustness to environmental mismatch since it depends only on horizontal wavenumber differences multiplied by the *change* in target range.

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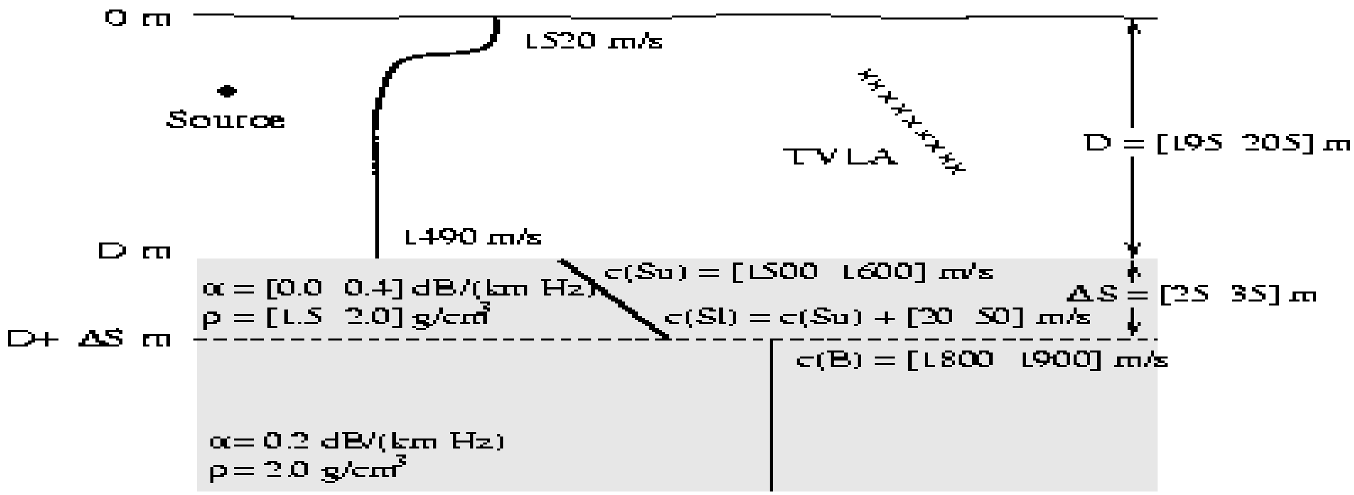
Conventional MFP with a Vertical or Horizontal Array



- A snapshot of tilted vertical linear array (TVLA) data can be modeled as:

$$x_n = s_n U(q_s) a + h_n$$

where $[U(q_s)]_{ml} = f_l(z_m) e^{-jk_l md \sin g \sin q_s}, [a(r_s, z_s)]_l = f_l(z_s) e^{-jk_l r_s}$,

q_s, r_s, z_s are source bearing, range, depth, and g is array tilt.

- Full 3-D range-depth-bearing adaptive MFP requires accurate prediction of $(k_l - k_j) r_s$ which is difficult for large range, sufficient observation time over which the source can be considered stationary, and a search over 3 variables.

Some Previous Depth Estimation Approaches

- Averaging a 3-D MV surface over range may be computationally intensive. Further, matrix inversion prior to averaging can be statistically unstable.
- Matching the normal mode power distribution versus hypothesized target depth requires near orthogonality between modes at the array.
- The MV adaptive beamformer with extended range constraints (MV-ERC) consists of widening the range mainlobe so that bearing-depth estimation can be performed in coarse range bands.
- Desensitizing the adaptive beamformer to target range variation permits the use of longer observation times for more stable CSDM estimation.
- The ambiguity surface for the MV-ERC beamformer is given by:

$$Z_{ERC}(r,z) = \mathbf{e}_1^{+}(\mathbf{H}(r,z)^{+}\mathbf{R}_x\mathbf{H}(r,z))^{-1}\mathbf{e}_1$$

where $\mathbf{e}_1 = [1,0,\ldots,0]^{+}$, where $\mathbf{H}(r,z)$ are the dominant eigenvectors of $\frac{1}{\mathrm{N}}\sum_{k=1}^{N}\mathbf{d}(r+\Delta_k,z)\mathbf{d}(r+\Delta_k,z)^{+}$ and $\Delta_k, k=1,\ldots,N$ defines a coarse range band around r.

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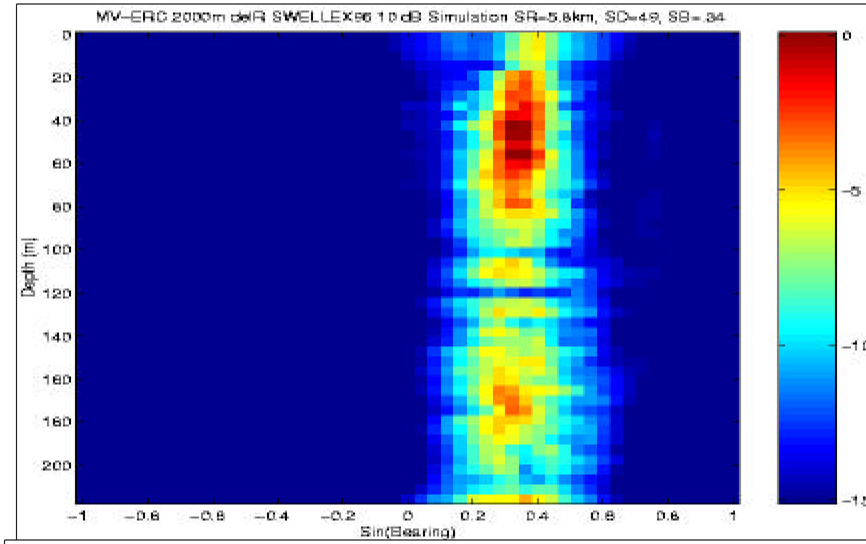
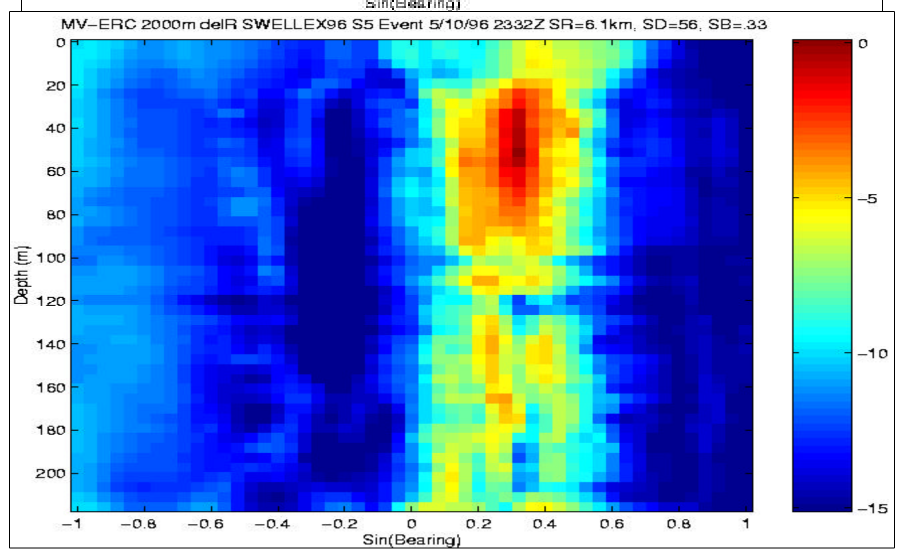
MV-ERC Matched-field Beamforming Results

- Typical *simulated* ambiguity surface for 8-tonal SWELLEX-96 TVLA scenario with SR=5800 m, SD=49 m. and SB = asin(0.34).





- Typical *real* ambiguity surface for 8-tonal SWELLEX-96 TVLA event S5 5/10/96 2332 Z. Obs. Time = 54 s, SR=6100 m, SD=56 m, and SB=asin(0.33).

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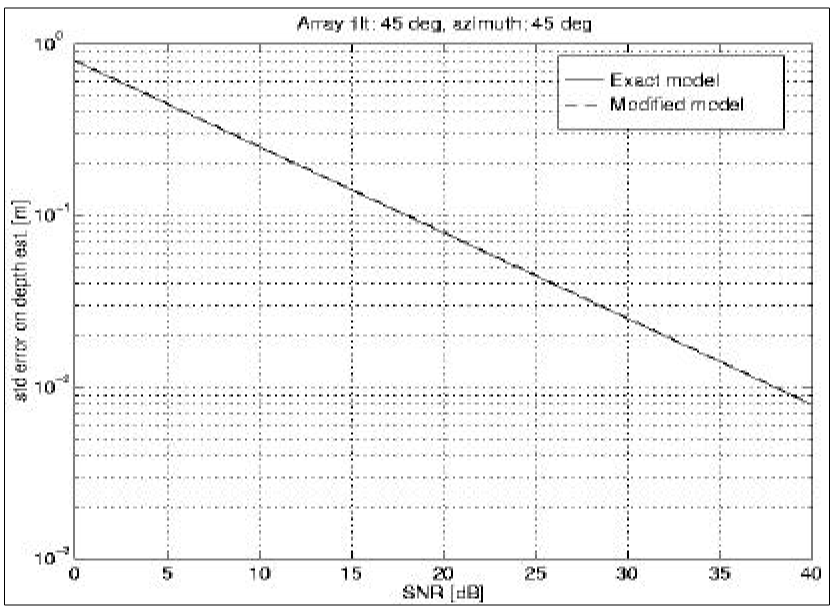
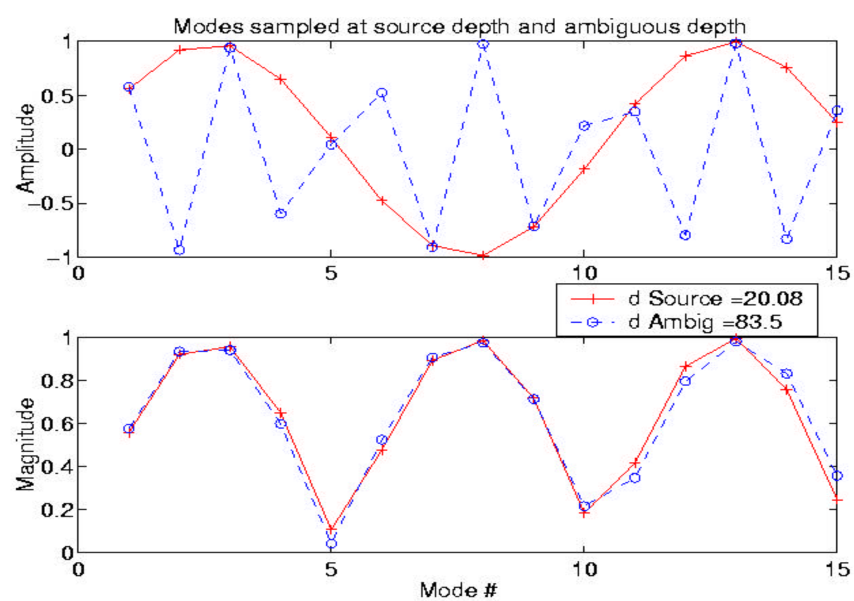
Fundamental Depth Estimation Considerations

- Robust bearing-depth discrimination without range could in principle be obtained by treating modal phase terms as nuisance parameters, i.e. $[a(r_s, z_s)]_l = f_l(z_s)e^{-jJ_l}$
- Cramer-Rao Lower Bound (CRLB) on source depth (left) for the known (“exact”) versus unknown (“modified”) modal phase suggests depth estimation without range possible.
- Sampled modal eigenfunctions (right) sampled at two depths illustrate ambiguity in estimating modal phases jointly with source depth without target motion.





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A Dynamical Model for Passive Depth Estimation

- Idea is to exploit modal phase trajectory under a constant range-rate hypothesis in order to jointly estimate target range-rate and depth.

- Letting the complex range-dependent modal amplitudes of a source for snapshot *k* be denoted x_k, the relative changes in modal phase from snapshot-to-snapshot impose a Markov state update:

$$x_k = A_k(\dot{r})x_{k-1} + v_k$$

where $A_k(\dot{r}) \cong diag(e^{jk_l(r_k - r_{k-1})}) = diag(e^{jk_l \dot{r}(t_k - t_{k-1})})$ and the additive process noise approximately accounts for horizontal wavenumber uncertainties.

- The spatial wavefront at the array, y_k, at narrowband snapshot *k*, is then obtained by taking the sum of the normal modes multiplied by an i.i.d. zero-mean Gaussian random scalar, s_k:

$$y_k = s_k U(q_s)\Phi(z_s)x_k + h_k$$

where $\Phi(z_s) = diag(f_l(z_s))$ and h_k represents additive noise.

A Recursive Resampled Bayesian Estimate for Depth

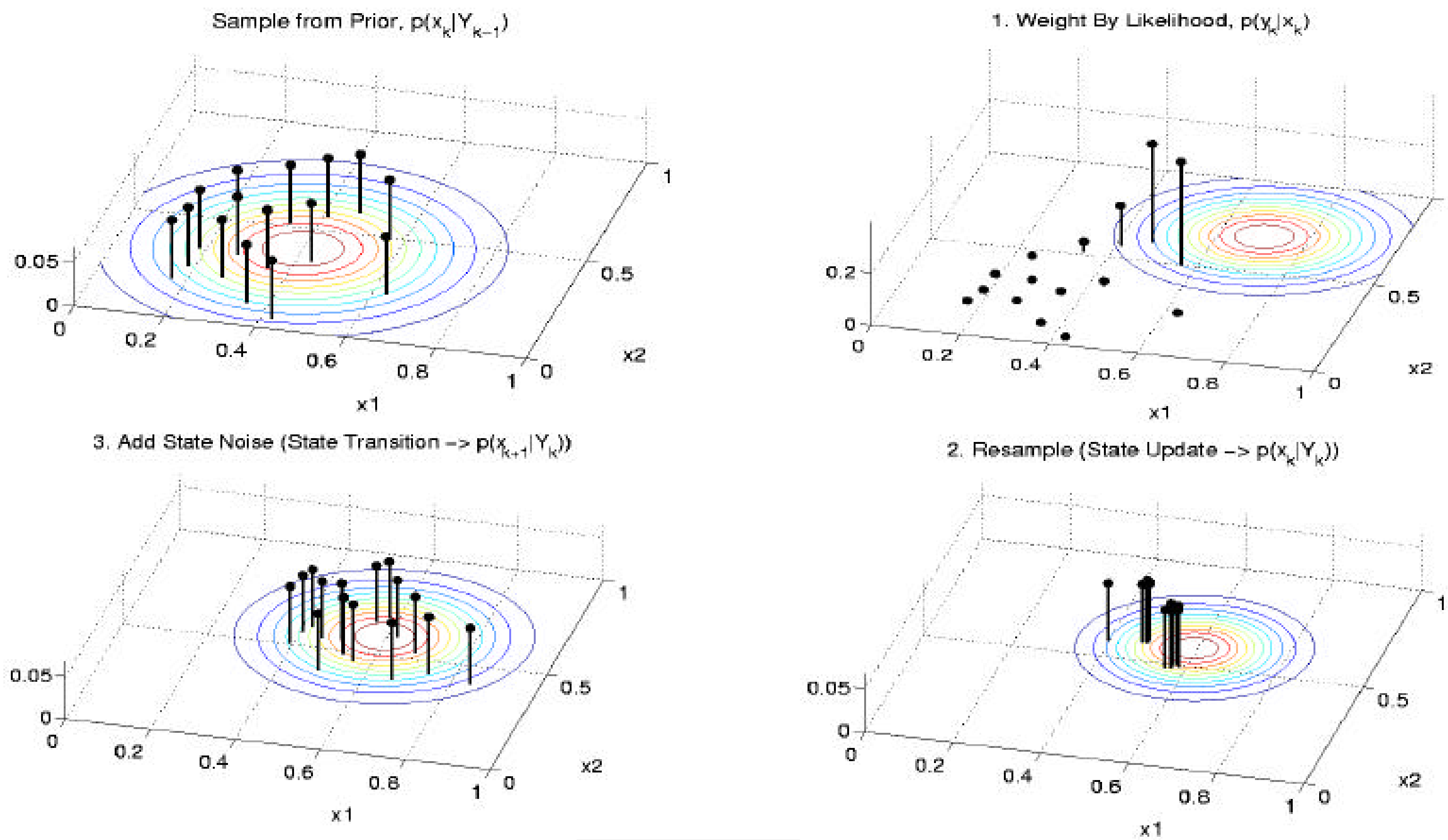
- The non-linear depth-range-rate estimation problem can be solved by representing the posterior density function of the state by a *set of random samples*, rather than a continuous function over some high dimensional state space.
- For example, suppose at step k, random samples, $x_{k-1}(i)$, $i = 1,\ldots,N$, are available from $p(x_{k-1}|y_1,\ldots,y_{k-1})$. Then samples, $x_k^*(i)$ from $p(x_k|y_1,\ldots,y_{k-1})$ can be obtained using these samples as input to the state equation together with samples, e_{g_k}, drawn from its known distribution.
- The updated posterior density can then be approximated at each sample, $x_k^*(i)$, by forming:

$$q_i = \frac{p(y_k|x_k^*(i))}{\sum_{j=1}^{N} p(y_k|x_k^*(i))}$$

- Samples, $x_k(i)$, $i = 1,\ldots,N$, can now be obtained by bootstrap resampling N times from the discrete distribution defined such that for any j, $\Pr\{x_k(j) = x_k^*(i)\} = q_i$. The conditional mean of the depth parameter, z_k, can then be estimated by averaging these bootstrap samples.
- These steps are repeated for each range step to obtain a recursive estimate.
- For passive sonar, $p(y_k|x_k, z_s)$ is zero-mean Gaussian with covariance $R_k = s_s^2 U\Phi(z_s)x_k x_k^+ \Phi(z_s)^+ U^+ + s^2 I$ as in conventional models.

Sequential Importance Sampling Illustration

- Illustration clockwise from upper left of random samples from prior, weighting by likelihood function, Monte Carlo re-sampling from updated posterior, prediction using random samples of state noise.



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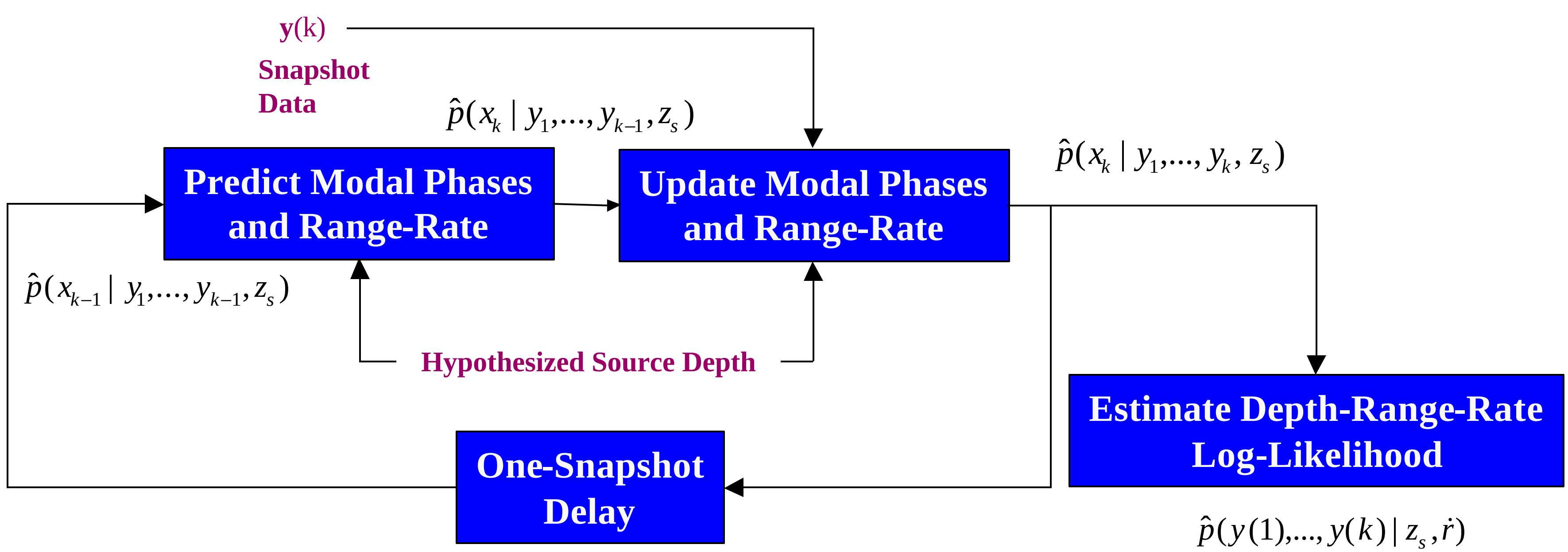
Recursive Bayesian Passive MTDE Summary

- State vector includes unit-magnitude modal coefficients and range-rate with uniform prior.
- State transition density assumes multiplicative modal phase noise.
- Conditional density of data snapshot given state vector is zero-mean complex Gaussian.
- Estimates of depth-range-rate likelihood achieved using sequential importance sampling.



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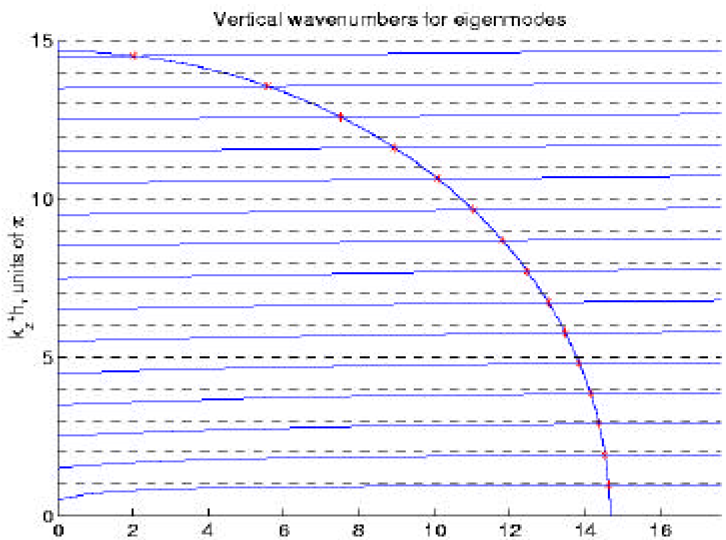
Mismatched Range-Independent Simulation

- To illustrate passive moving target depth estimation, a simple simulation was performed using a normal mode model of a 15-mode Pekeris waveguide with a 100 m. waveguide.
- Simulation of 0 dB SNR targets, at 2 m. and 20 m. depths with 2 m/s range-rate, received at a water-column spanning 23 sensor vertical array using ~50 narrowband snapshots was considered.
- Large environmental uncertainty was simulated by adding independent uniform random variables to the Pekeris vertical wavenumbers, $k_z = k_z^0 + \Delta k_z$, where $\Delta k_z = U(-0.45\pi/h, 0.45\pi/h)$ used to compute both horizontal wavenumbers and modal depth eigenfunctions.



Mode Number

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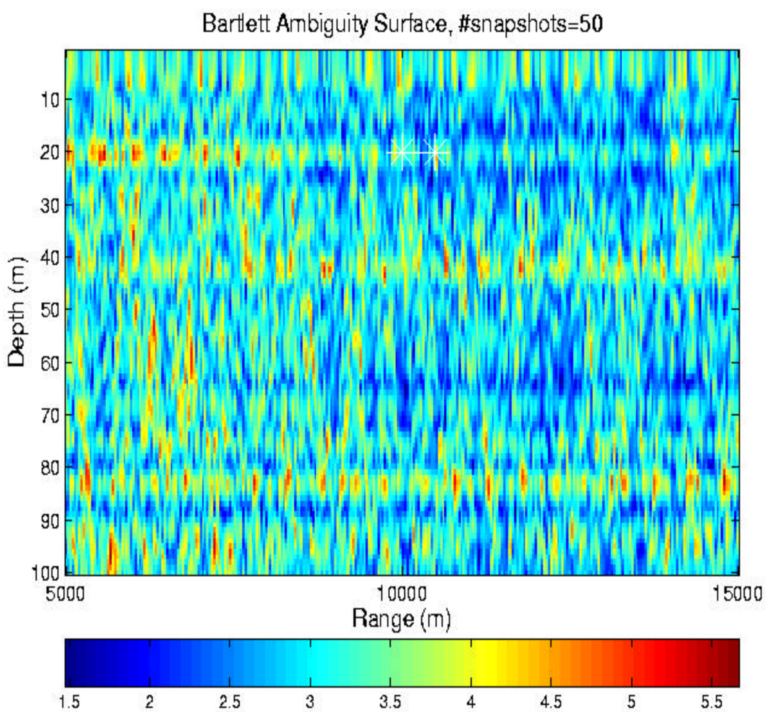
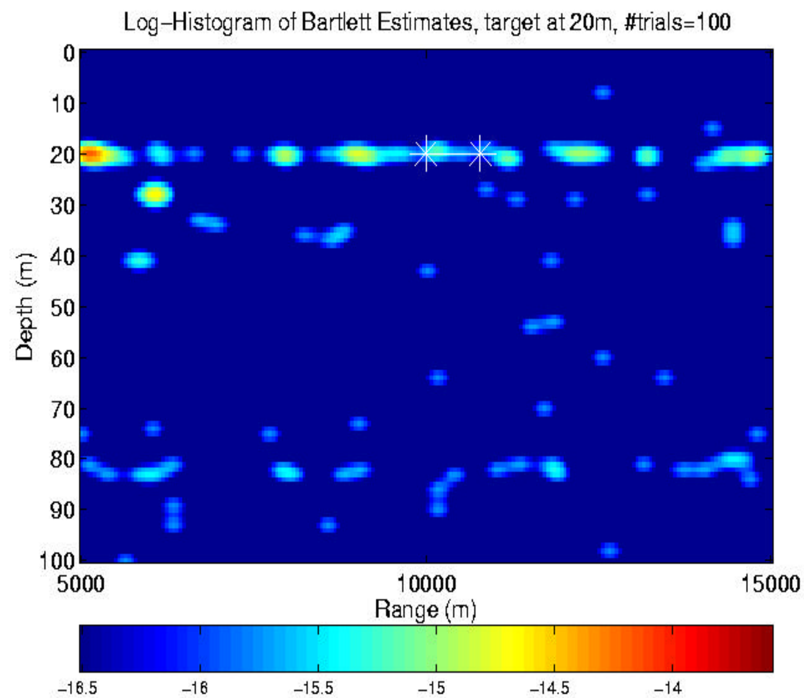
Mismatched Conventional MFP for a Submerged Source

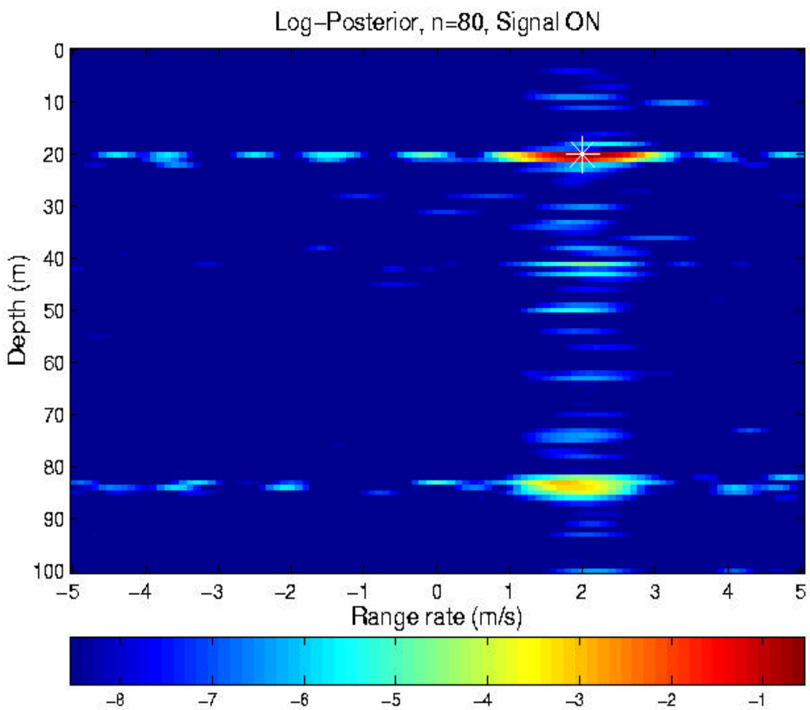
- Example conventional (aka “Bartlett”) ambiguity surface (left) for moving source at 20 m. depth illustrates extreme ambiguity problem.
- Log-histogram (right) of MFP estimates using 100 Monte Carlo trials illustrates poor range estimation and mediocre depth estimation performance over $\Delta k_z = U(-0.45p/h, 0.45p/h)$

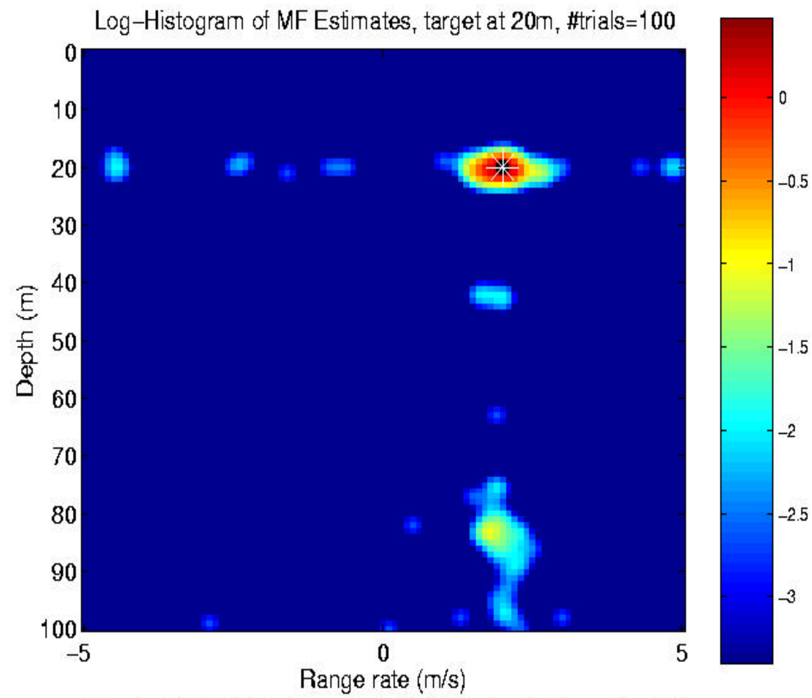




Mismatched Passive MTDE for a Submerged Source

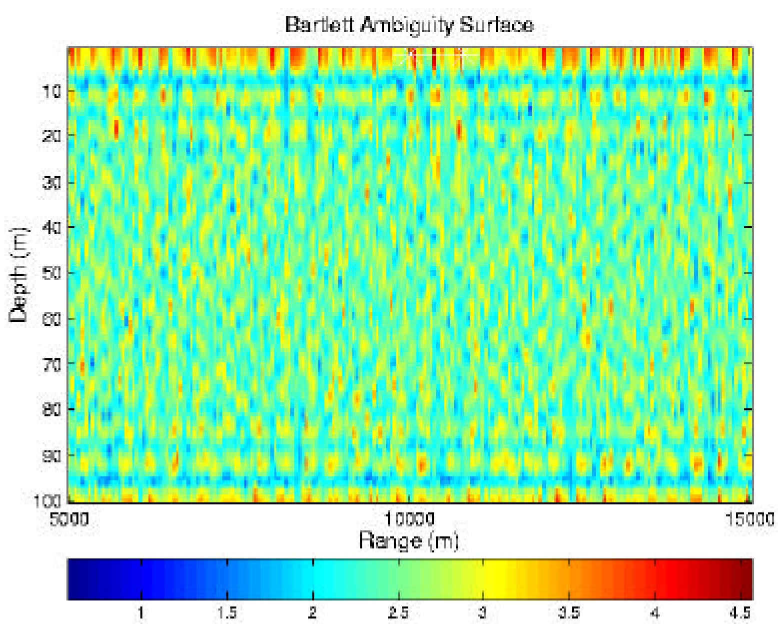
- Example depth-range-rate log-likelihood surface (left) for moving source at 20 m. depth illustrates depth ambiguity with excellent range-rate estimation.
- Log-histogram of MTDE (right) over 100 Monte Carlo trials illustrating joint depth-range-rate estimation performance over $\Delta k_z = U(-0.45p/h, 0.45p/h)$

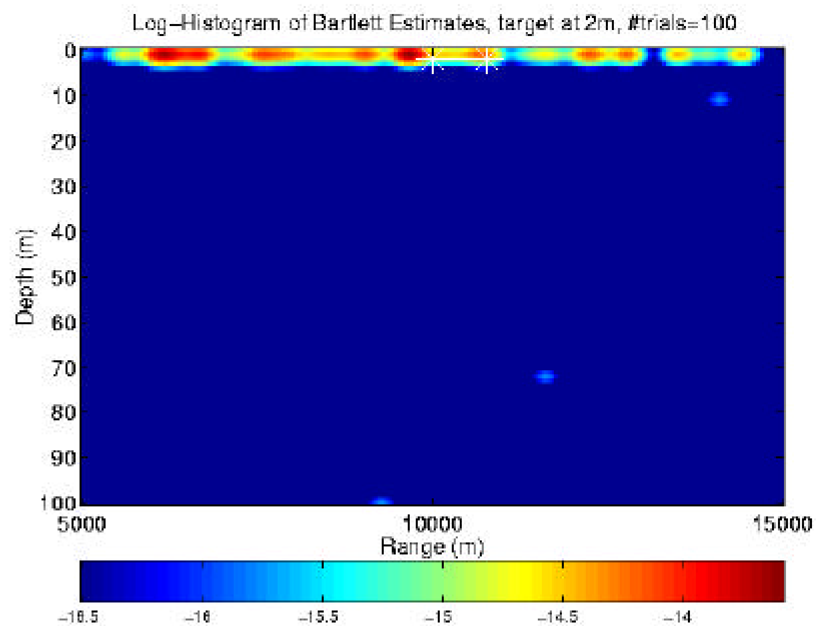




Mismatched Conventional MFP for Near-Surface Source

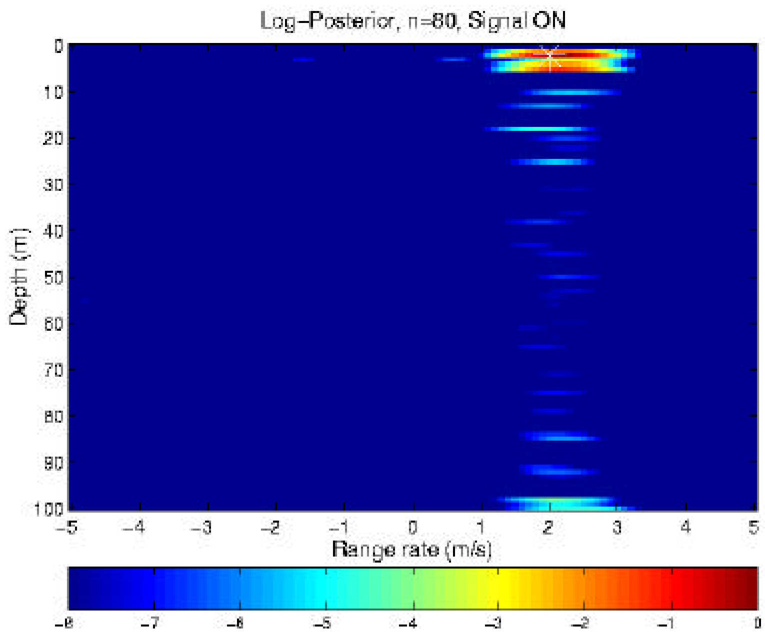
- Example conventional (aka "Bartlett") ambiguity surface (left) for moving source at 2 m. depth and 2 m/s range-rate illustrates extreme range ambiguity problem.
- Log-histogram (right) of MFP estimates using 100 Monte Carlo trials illustrates poor range estimation but good depth estimation performance over $\Delta k_z = U(-0.45p/h, 0.45p/h)$
- In practice, *detection* of a moving source from uncorrelated surface-based noise seriously limits the use of conventional MFP for depth classification.

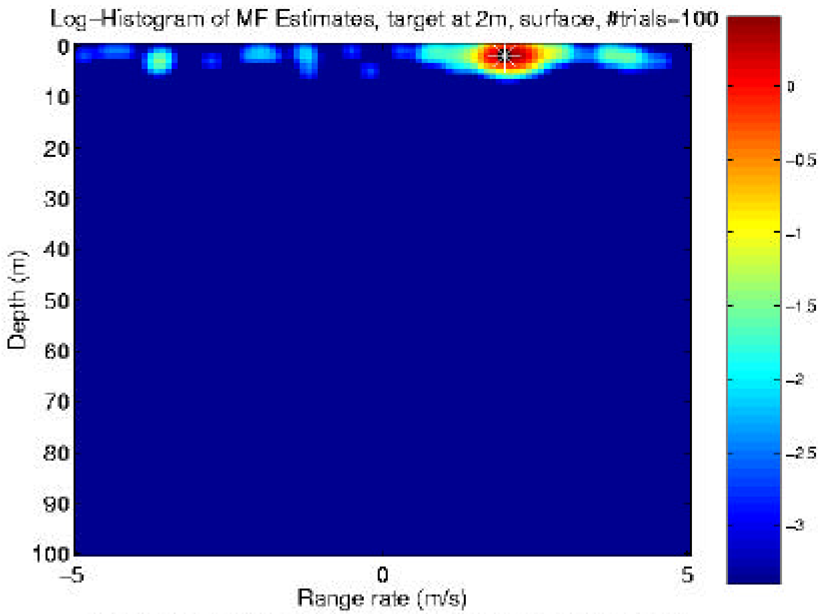




Mismatched Passive MTDE for a Near-Surface Source

- Example depth-range-rate log-likelihood surface (left) for moving source at 2 m. depth illustrates depth estimation comparable to MFP with excellent range-rate estimation.
- Log-histogram of MTDE (right) over 100 Monte Carlo trials illustrates good range-rate estimation and depth estimation performance over $\Delta k_z = U(0,0.9p/h)$
- Ability of passive MTDE to discriminate constant range-rate sources may facilitate detection of targets at depth from surface shipping with different range-rates.





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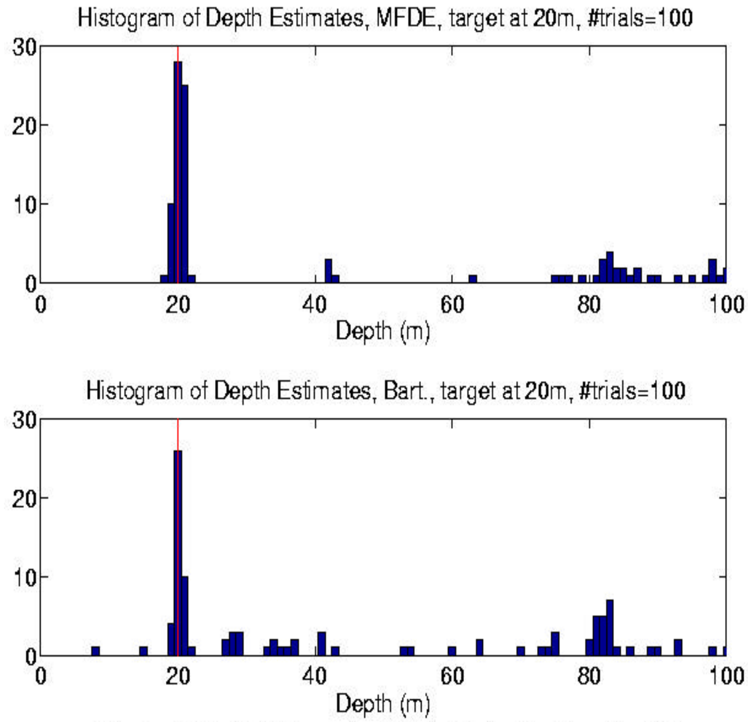
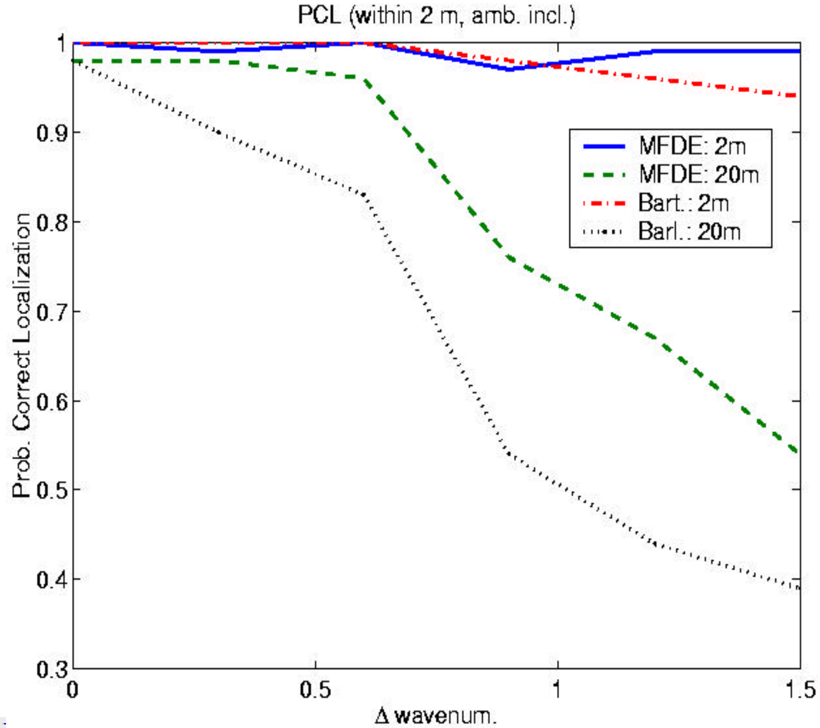
Comparison of Depth Estimation Performance

- Histograms of MTDE (upper left) vs. conventional (lower left) for submerged source with $\Delta k_z = U(-0.45p/h, 0.45p/h)$ mismatch indicates moderately improved performance.
- Probability of correct depth localization (notwithstanding range, range-rate, or predicted depth ambiguity) compares performance for surface versus submerged source.
- Joint PCL for MFP range-depth estimate versus MTDE range-rate-depth estimate expected to show significant improvement for latter approach in mismatched channels.





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Conclusions and Future Work

- Moving target depth estimation (MTDE) shows potential as a classification tool for passive discrimination of sources in the water column versus surface ships.
- By exploiting target motion, MTDE jointly estimates depth and range-rate avoiding severe range ambiguity problems of conventional MFP in mismatched conditions.
- Current sequential importance sampling approach for solving MTDE requires further development for operation at lower signal-to-noise ratios.
- MTDE framework may provide an alternative detection strategy by considering bearing-range-rate-depth likelihood surfaces.
- Current work includes evaluating MTDE with real SACLANT and SWELLEX data.
- Straightforward broadband passive implementation can be achieved by incoherently summing a posteriori probabilities across the frequency band.